

Extreme Sahel heatwave that hit highly vulnerable population at the end of Ramadan would not have occurred without climate change

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Main Findings

- While Burkina Faso and Mali are both countries with populations that are acclimated to high temperatures, the length and severity of this heatwave made it difficult for people to cope, as evidenced by the reported increased hospitalisations and deaths. Heatwaves are amongst the deadliest natural hazards with thousands of people dying from heat-related causes each year and many more suffering other severe health and livelihood consequences. Many places lack good record keeping of heat-related deaths, therefore currently available figures are likely an underestimate.
- This heatwave coincided with Ramadan (fasting) and power cuts, which compounded the risk for vulnerable groups and even those not traditionally considered vulnerable. Even minimum temperatures, overnight, remained relatively high, making it so that people did not get a break from the heat. The power cuts further made it difficult for those who did have access to mechanical cooling to use it, thus reducing their coping capacity.
- Even in today's climate, that has warmed by 1.2°C since pre-industrial times due to human activities, the extreme heat observed over the Mali/Burkina Faso region is still rare. While the daily temperatures were extreme, with a return time of about 100 years, the 5-day maximum temperatures were particularly unusual with a return time of 200 years. Minimum temperatures were less extreme but still rare with a return time of 20 years over Mali/Burkina Faso. For the Sahel region the return time of the 5-day maximum temperatures are 30 years.
- To estimate the influence that human-caused climate change has had on the extreme heat since the climate was 1.2°C cooler, we combine climate models with observations. Observations and models both show that heatwaves with the magnitude observed in March and April 2024 in the region would have been impossible to occur without the global warming of 1.2°C to date.
- Extreme 5-day maximum heat as rare as the observed event over Mali/Burkina Faso would have been 1.5 °C cooler and 1.4 °C cooler over the larger Sahel region if humans had not warmed the planet by burning fossil fuels. For minimum temperatures over Mali/Burkina Faso the change in intensity is even larger: in a 1.2°C cooler climate the extreme
- These trends will continue with future warming. Over Mali/Burkina Faso a heatwave like the observed event would be another 1°C hotter in a 0.8°C warmer world (2°C global warming since pre-industrial times). An event of the same magnitude as observed in 2024 would then not be very rare anymore but occur 10-times more frequent than in today's climate.
- We also assessed whether the current El Niño event had an influence on the extreme temperatures and found that while there is some contribution it is small compared to human-induced climate change, explaining about 0.2°C of the observed 5-day heat event.
- Rapid urbanization and loss of green spaces in cities such as Bamako and Ouagadougou have increased the urban heat island effect. Coupled with high vulnerability, this highlights the need for sustainable urban planning that integrates green spaces, and building designs that account for high temperatures.
- Critical infrastructure such as electricity, water, and healthcare systems needs to be strengthened to adapt to the increasing frequency and intensity of extreme heat, requiring increased investment to ensure reliable access and service delivery.

1 Introduction

At the end of March and the beginning of April 2024, a very large region across North Africa and the Sahel experienced extreme heat, with maximum temperatures in the Sahel reaching 45°C and more and minimum temperatures of 32°C in Burkina Faso (Burkina Faso Meteorological Agency). Kayes in Mali recorded a maximum temperature of 48.5°C on the 3rd of April (Mali Meteorological Agency). Very high maximum temperatures were also recorded in Senegal, with several cities reporting temperatures well above 40°C over the first week of April (Senegal Meteorological Agency).

The extreme heat follows a series of global record breaking hot months that saw the hottest ever March ([C3S, 2024](#)) as well as hottest ever February ([C3S, 2024](#)), both with very high temperatures in large parts of Africa, that also led to unseasonable high heat indices ([WWA, 2024](#)).

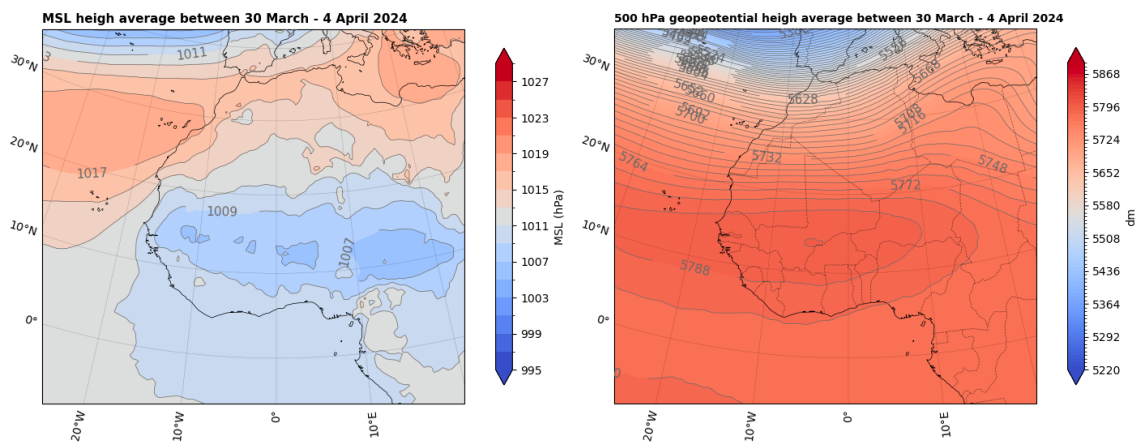


Figure 1: Mean sea level pressure (left) and 500hPa geopotential height over the Sahel during the period 30th March to 4th April 2024.

The heatwave was caused by a heat low over the most affected region (fig. 1)) stretching from the Eastern coast of Senegal to Chad. On the 23rd of March, the intrusion of a Rossby wave led to the formation of an upper level trough centred off the Morocco coast and extending south towards southern Mauritania (Figure 2), leading to the well-known tropical plume

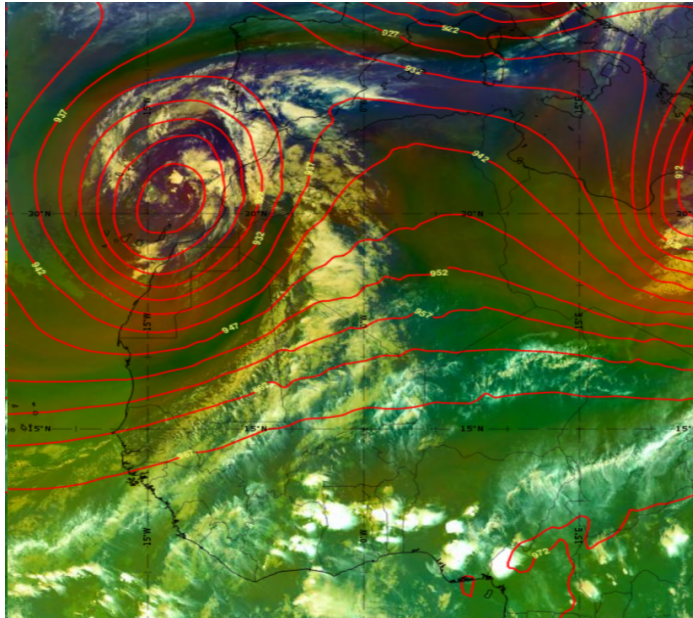


Figure 2: *Airmass satellite imagery superimposed with 300 hPa geopotential height on 23 March 2024 at 18:00Z. Source: Eumetrain*

The plume led to low level moisture converging into the Sahel (Figure 3), along with a progressive rise in temperatures. The following days the Rossby wave weakened and moved slowly eastward. Figure 3 (left) also shows a reinforcement of convection from 30 March further South in the Gulf of Guinea, likely as a result of a convective phase of the Madden Julian Oscillation (MJO) crossing the region. This further pushed more moisture into the low layers of the Sahelian atmosphere, with a maximum anomaly in southwestern Mali around the Circle of Kayes. This anomalous moisture then interacted with the intense solar radiation to strengthen the West Africa Heat Low (see red contours on Figure 3 (right)), leading to the peak of the heat wave between 01 and 05 April. The following days, the convective activity of the MJO reached the Sahel leading to important rainfall events across the region with Ouagadougou in Burkina Faso for example recording 60 mm on 06 April (daily bulletin of ANAM-Burkina Faso). This eventually ameliorated the heat conditions..

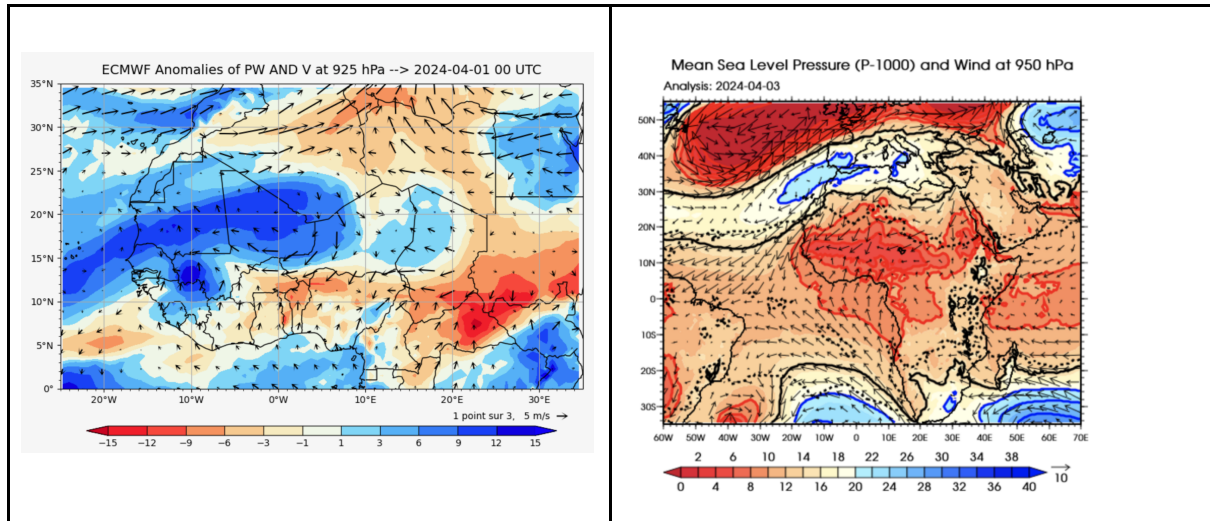
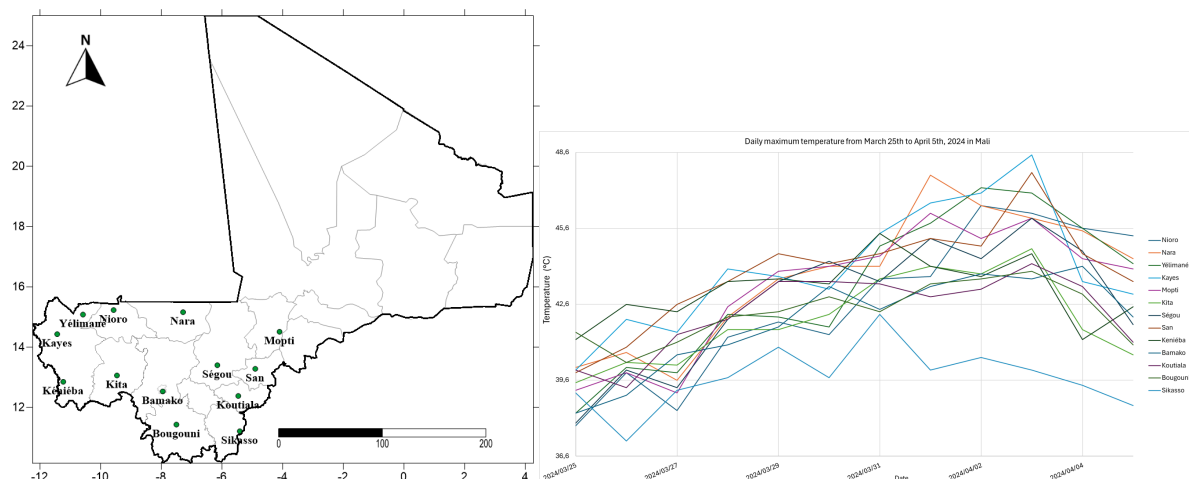


Figure 3: Anomalies of precipitable water and wind at 925 hPa from ECMWF on 01 April 2024 (left) and Mean sea level pressure (minus 1000 hPa) and wind at 950 hPa on 03 April 2024.(right). Source: MISVA

1.1 Event definition

Figure 4 shows the evolution of the heat wave for weather stations in Mali and Burkina Faso, showing the heat peaking between the 31st of March and the 4th of April, when the most severe impacts were recorded. Figure 5a shows these 5-day maximum temperatures while figure 5b shows the period for which the highest temperatures were recorded over North Africa and Sahel. While temperatures were extreme over this larger region, the highest temperatures were recorded in Mali and Burkina Faso and along a large region encompassing Senegal, Guinea, Mali, Burkina Faso, Niger, Nigeria and Chad. To focus on the most affected region as well as recognising the spatial extent of the event we use two spatial domains for further analysis: the southern part of Mali and Burkina Faso (fig. 5a, black outline) and a box covering the parts of the countries mentioned above (fig. 5b, black outline) where the heat was most extreme, including the Sahel region. While records were also recorded in North Africa, extending the region further north would have meant including regions with a different seasonal cycle and thus different climatological characteristics.



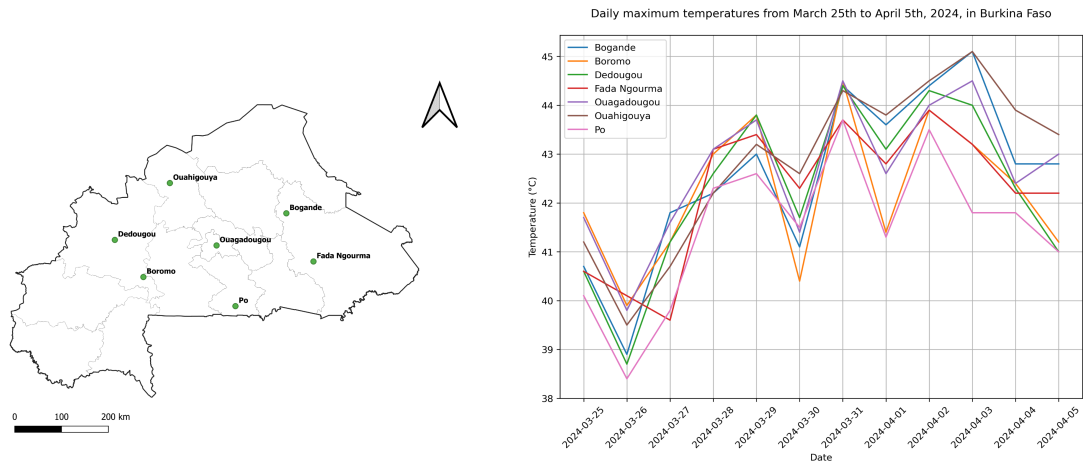


Figure 4: Evolution of daily maximum temperature from March 25th to April 5th, 2024, in Burkina Faso and Mali using in situ data.

For the temporal event definition we focus on 5-day averages of maximum, and in the case of the smaller region also minimum temperatures.

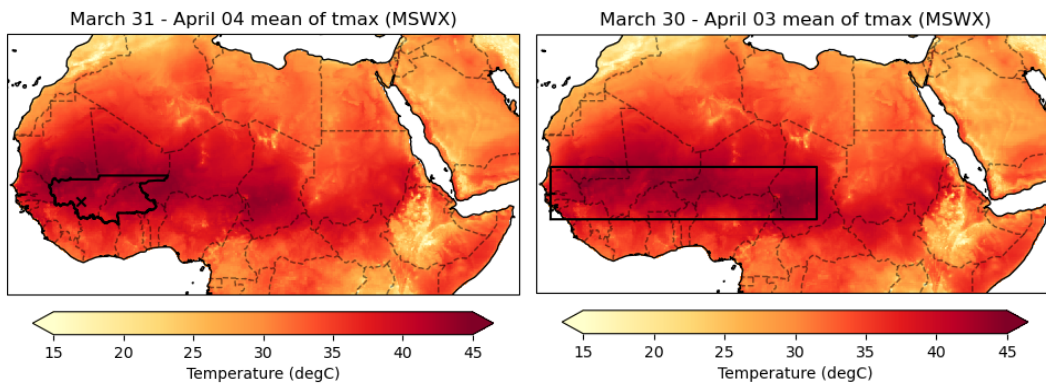


Figure 5: 5-day average anomaly of daily maximum temperature for (a) the period of 31st of March to 4th of April 2024 and (b) the period of 30th of March to 3rd of April 2024. The black outline in a) and box in b) show the study regions.

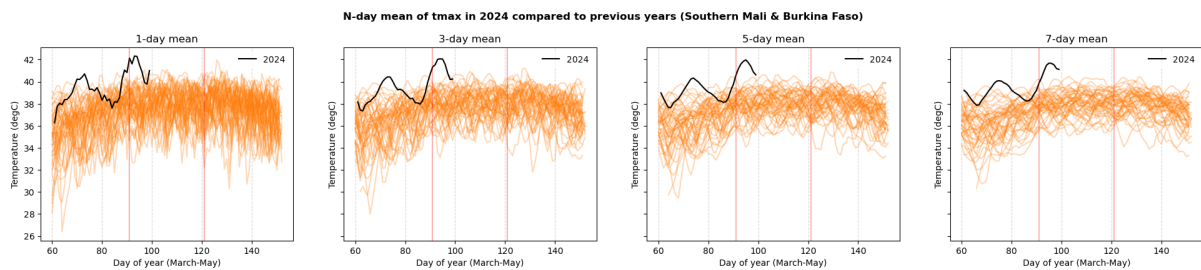


Figure 6: 1-, 3-, 5- and 7-day rolling mean of tmax over southern Mali and Burkina Faso in MSWX. Days between the two red vertical lines are April days.

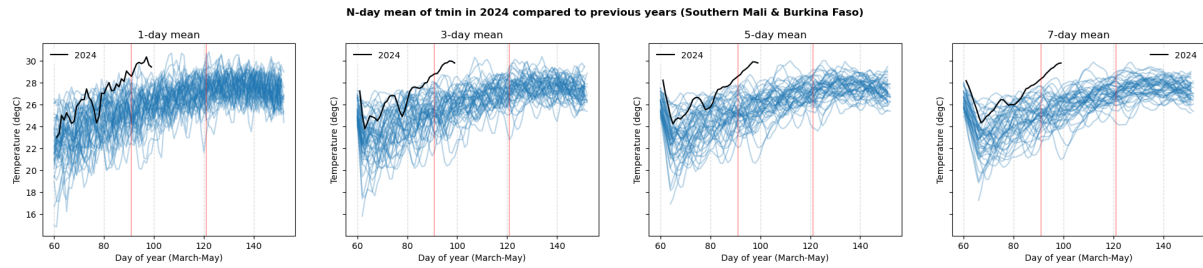


Figure 7: 1-, 3-, 5- and 7-day rolling mean of tmin over southern Mali and Burkina Faso. Days between the two red vertical lines are April days.

Figures 6 and 7 show the maximum and minimum temperatures averaged over 1, 3, 5 and 7 days for the Mali/BF region. From the orange lines in figure 6 representing all previous years in the data set it is apparent that the seasonal peak occurs usually somewhere in all three months from March to May, while the blue lines in figure 7, representing all previous minimum temperatures in the region show a peak in May. To focus the study on the particular event we thus use April maxima only.

1.2 Literature

Extreme temperatures have increased globally since 1950 and across most land areas including the Sahel, North and West Africa ([Seneviratne et al., 2021](#)). Observations reveal a clear increase in the intensity and frequency of hot days over these regions ([Dunn et al., 2020](#), [Perkins-Kirkpatrick and Lewis, 2020](#)). Despite the lack of formal attribution studies dedicated to this region, observed trends in temperature have been attributed to human-induced climate change ([Seneviratne et al., 2021](#)). Previous studies have assessed that for the spring season, the Sahel could experience a “permanent heatwave” under future climate change ([Sambou et al., 2021](#)).

The boreal spring period from March-June brings the hottest temperatures to the Sahel region. Overall temperatures in the Sahel countries have significantly increased over the 20th and early 21st centuries ([Yobom, 2020](#)). This has been accompanied by a rise in the frequency, duration and intensity of heatwaves ([Oueslati et al., 2017](#); [Moron et al., 2016](#)). Increases are observed across both day-time and night-time mean temperatures, in the frequency of events above the 90th percentile, and in very hot days and tropical nights, defined above 35 C and 20 C , respectively ([Moron et al., 2016](#)). This indicates a monotonically shifting distribution of temperatures with warming ([Sambou et al., 2021](#)).

Night-time temperatures show a stronger rate of increase than day-time temperatures ([Ringard et al., 2016](#)). This is due to different mechanisms driving maximum and minimum temperatures. Daily maximum temperatures are driven by increases in shortwave radiation associated with reductions in cloud cover, while minimum temperatures are driven by increases in longwave radiation due to the influence of water vapour, typically advected from the Guinea coasts and Atlantic ocean ([Oueslati et al., 2017](#); [Sambou et al., 2021](#)). For this reason, simultaneous occurrences of very high maximum and minimum temperatures are rare in the Sahel ([Sambou et al., 2021](#)). Dynamical configurations leading to extreme conditions have not changed significantly in frequency, suggesting that similar configurations are leading to warmer anomalies due to thermodynamical changes ([Sambou et al., 2021](#)). Projections of future warming suggest further rapid increases in heatwaves, with the magnitude of increase heavily dependent upon the emissions scenario ([Sambou et al., 2021](#)).

Even though there is overwhelming evidence for an increase in heatwaves since the 1950s, only very few have been reported in Africa ([Otto and Harrington, 2020](#)), highlighting a dangerous lack of awareness of the increase in extreme heat and associated heightened mortality and morbidity particularly for vulnerable populations, including the elderly, outdoor workers and children, or people with chronic conditions (notably respiratory, cardio, renal, cerebral vascular and/or mental health) may suffer more physical and mental health impacts of exposure to extreme temperatures ([Li et al. 2015](#); [Carleton, 2017](#); [Swain et al. 2019](#)). The very limited literature on extreme heat effects in the Sahel tends to show strong impacts on the health of the elderly ([Sy et al 2022](#)), young children ([Diboulo et al. 2012](#)), pregnant/lactating women ([Kadio et al 2023](#)) and people with preexisting health conditions ([Somdakouma et al. 2024](#)) as well as on the water and energy sector ([Ndiaye et al. 2017](#)).

2 Data and methods

2.1 Observational data

Daily maximum and minimum temperatures are taken from three gridded observation data products. While results are presented for all three products in Section 3, we note that the ERA5 data is provisional at the time of writing, while recent values of minimum temperatures in CPC are inconsistent with the high temperatures reported; we therefore prioritise the MSWX dataset in this analysis, and all maps are produced using MSWX data.

1. The ERA5 reanalysis product ([Hersbach et al., 2020](#)) produced by the European Centre for Medium-Range Weather Forecasts. This product covers the globe at 0.25° resolution, starting in 1950. The variables from ERA5 are not directly assimilated, but are generated by atmospheric components of the Integrated Forecast System (IFS) modelling system. Reanalysis data is available until the end of March 2024, extended to April 9th with ECMWF analysis data.
2. The CPC Global Unified Daily Gridded data, which covers the globe at 0.5° resolution, for the period 1979-present. Data are available from [NOAA](#).
3. The Multi-Source Weather (MSWX) dataset ([Beck et al., 2022](#)), which combines various observational and reanalysis-based data for reliable bias-corrected weather variable estimates, at 3-hourly intervals from 1979 to near real-time, and at 0.1° spatial resolution globally.

As a proxy for anthropogenic climate change we use the (low-pass filtered) global mean surface temperature (GMST) taken from the National Aeronautics and Space Administration (NASA) Goddard Institute for Space Science (GISS) surface temperature analysis (GISTEMP, [Hansen et al., 2010](#) and [Lenssen et al., 2019](#)).

The detrended Niño3.4 index is computed from [NOAA's ERSST v.5](#) sea surface temperatures, by subtracting the mean tropical SST (20S-20N) from the mean SST over the Nino3.4 region (5S-5N, 170W-120W).

2.2 Model and experiment descriptions

We use 17 simulations from the CMIP6 ensemble ([Eyring et al., 2016](#)). For all simulations, the period 1850 to 2015 is based on historical simulations, while the SSP5-8.5 scenario is used for the remainder of the 21st century.

2.3 Statistical methods

Methods for observational and model analysis and for model evaluation and synthesis are used according to the World Weather Attribution Protocol, described in [Philip et al. \(2020\)](#), with supporting details found in [van Oldenborgh et al. \(2021\)](#), [Ciavarella et al. \(2021\)](#) and [here](#). The key steps, in sections 3-6, are: (3) trend estimation from observations; (4) model validation; (5) multi-method multi-model attribution and (6) synthesis of the attribution statement.

In this analysis we examine time series of annual maxima of the 5-day average of daily maximum temperatures during April (tx5x) over both the Mali-Burkina Faso and wider Sahel regions (Figure 5); and annual maxima of the 5-day average of daily minimum temperatures during April (tn5x) over the Mali-Burkina Faso region.

A nonstationary generalised extreme value distribution (GEV) is used to model these variables: the distribution is assumed to shift linearly with GMST, while the variance remains constant. Parameters are estimated using maximum likelihood.

For each time series we calculate the return periods, probability ratio (PR; the factor-change in the event's probability) and change in intensity of the event under study for the 2024 GMST and for 1.2C cooler GMST: this allows us to compare the climate of now and of the preindustrial past (1850-1900, based on the [Global Warming Index](#)).

3 Observational analysis: return period and trend

3.1 Analysis of gridded observational data products

3.1.1 tx5x in southern Mali & Burkina Faso

Figure 8 shows the time series of April tx5x over the southern Mali/Burkina Faso region in three gridded data products, with the fitted GMST-dependent trend overlaid. The GMST-dependent trend (black line) closely resembles a local regression line fitted over time (red line), suggesting that the fitted model captures the temporal trend well. The three datasets differ in their mean levels but all show a clear upward trend in 5-day maximum temperatures. In all three datasets, the 2024 event is extreme, lying close to or above the upper blue line, which represents the expected magnitude of a once-in-40-year event; in CPC, the event has a return period of 231 years (95% confidence interval: 33, infinite); in ERA5, of 37 years (12, infinite); and in MSWX, of 264 years (34, infinite). However, we note that the

ERA5 data covering the period of the event was near-real-time analysis data, and may be likely to change when updated to reanalysis data. We therefore do not use ERA5 to determine the return period, and define this as a once-in-200-year event. However, when carrying out attribution using climate models, a 200-year return period produced a high proportion of infinite probability ratios; in order to obtain more stable results, we therefore use a more conservative return period of 100 years in the climate model attribution step. This also accounts for the much lower return period in the ERA5 dataset.

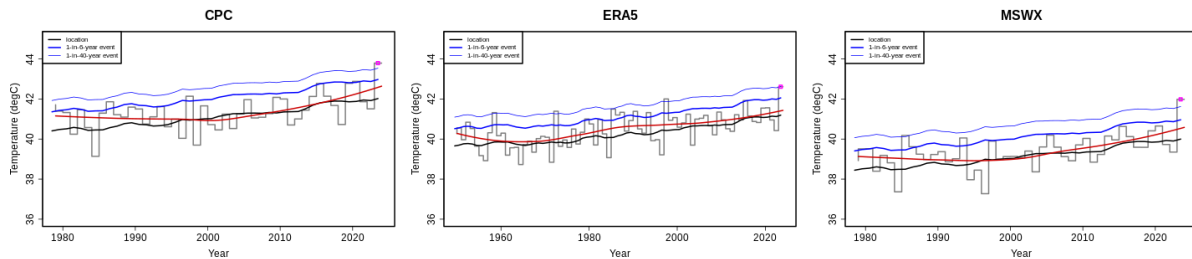


Figure 8: Time series of $tx5x$ (annual maxima of 5-day average of daily maximum temperatures averaged over southern Mali and Burkina Faso). The pink dot marks the 2024 event; the heavy black line indicates the mean of the fitted GEV model, and the blue lines indicate the expected return levels of 6- and 40-year events. The red line is a local regression.

As noted above, one particularly unusual aspect of the early April heatwave, which is likely to have contributed to the severity of the impacts, was its duration. However, the intensity of the heatwave was unusual even at shorter timescales. Table 1 shows the return periods of the 1-, 3- and 5-day averages of maximum temperatures, for both the April and March-May periods, in CPC and MSWX. The single hottest day had a return period of 173 in CPC and 121 in MSWX, reflecting the record-breaking heat experienced over much of the region. The return period of the 3-day heatwave is less certain, at 252 years in CPC and 136 in MSWX; however, the 5-day event is clearly much more unusual in both datasets. (A similar pattern is seen in ERA5, albeit with much lower return periods). We also note that return periods were similar whether with respect to April temperatures (top row) or the whole March-May season (bottom row). For this reason, we focus on April temperatures throughout the report, but expect that the results apply to the whole season.

Table 1: Return periods of 2024's 1-, 3- and 5-day mean of daily maximum temperatures, with respect to April and March-May climatologies, in CPC and MSWX.

	CPC			MSWX		
	1-day	3-day	5-day	1-day	3-day	5-day
April	173	252	231	121	136	264
March-May	82	205	206	115	139	329

Figure 9 shows the linear fitted trend plotted against the GMST covariate, rather than time as above. In CPC, 5-day maximum temperatures in the region have increased by 2.3C (95% confidence interval: 0.75, 3.26); in ERA5, by 1.64C (1.19, 2.14); and in MSWX, by 2.22C (1.22, 3.38).

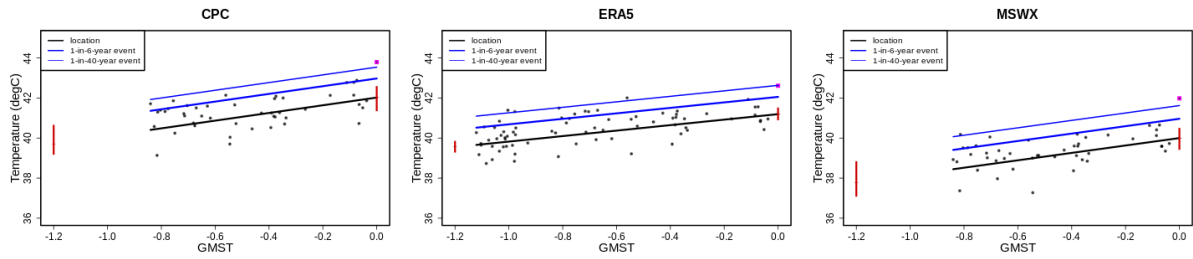


Figure 9: Linear trend in $tx5x$ over southern Mali and Burkina Faso as a function of GMST. The thick black line denotes the location parameter of the fitted distribution, and the blue lines show estimated 6- and 40-year return levels. The vertical lines show the 95% confidence interval for the location parameter for the 2024 climate and a hypothetical 1.2°C cooler climate. The 2024 observation is highlighted in magenta.

Figure 10 shows the modelled change in return levels due to a 1.2C change in GMST from the preindustrial to the current climate. The points representing the temperatures actually recorded in each dataset lie close to the lines representing the expected values, indicating that the statistical model fits the data well. In each dataset there is a clear separation between the return levels in the current climate (red) and the past climate (blue), and the pink dashed line representing the temperature of the observed event (pink dashed line) does not intersect with the blue line, indicating that an event of this magnitude would have been impossible in a preindustrial climate. Because of this, the best estimate of the probability ratio - that is, the factor change in the probability of such an event occurring - is infinite in all three datasets.

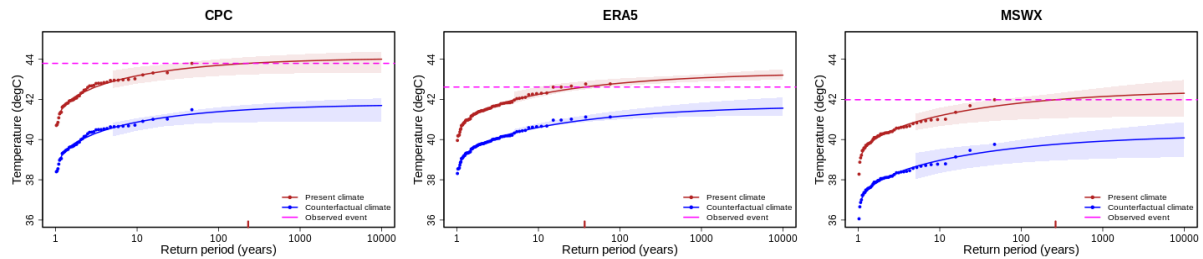


Figure 10: GEV-based return levels for $tx5x$ over southern Mali and Burkina Faso at 2024 GMST (red lines) and 1.2C lower GMST (blue line). Shaded regions represent 95% confidence intervals obtained via a bootstrapping procedure. The pink line shows the observed value of the 2024 event.

3.1.2 $tx5x$ in wider Sahel region

Similar results to those presented above were obtained for time series of maximum 5-day temperatures in the wider Sahel region bounded by the box in Figure 5. Figure 11 shows the time series of April $tx5x$ in each dataset. Again, all datasets exhibit an upward trend that is generally well modelled by GMST dependence, but the heatwave over this larger region is less extreme: 43 years in CPC (95% interval: 14, infinity), 7 years in ERA5 (4, 16), and 27 in MSWX (9, infinity). Again, we disregard the estimate from ERA5, and estimate the return period of this event to be approximately 30 years. The five-day maximum temperatures over this region have increased by 1.71C in CPC (95% interval: 0.61, 2.74); by 1.46C in ERA5 (1.03, 1.86); and by 1.81C in MSWX (1.01, 2.64). These changes are slightly smaller than those estimated for the smaller region in 3.1.1, suggesting that southern Mali and Burkina Faso may have warmed more than regions in the eastern Sahel. The probability ratios for this event are also very high: in CPC, the event was made 3332 times more likely by climate change (95% interval: 2, infinity); in ERA5, where the event was relatively moderate, 154 times more likely (12.9, infinity); and

in MSWX, the best estimate of the probability ratio was infinite. Plots of the linear trend in $tx5x$ as a function of GMST and of the effective return levels can be found in Figures A1 and A2 in the appendix.

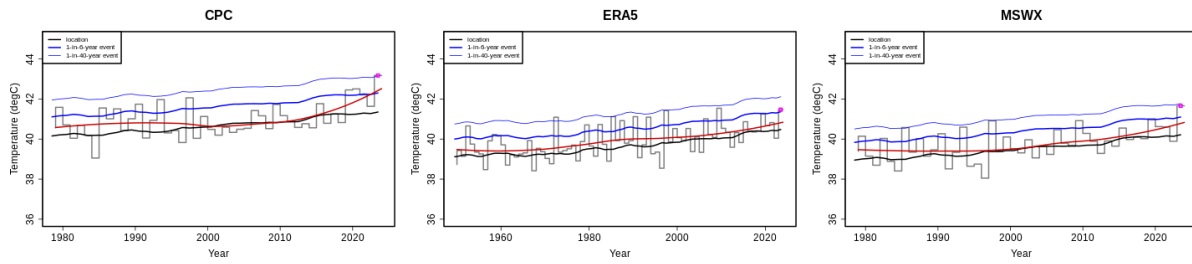


Figure 11: Time series of $tx5x$ (annual maxima of 5-day average of daily maximum temperatures averaged over the wider Sahel region, as shown in Figure 5). The pink dot marks the 2024 event; the heavy black line indicates the mean of the fitted GEV model, and the blue lines indicate the expected return levels of 6- and 40-year events. The red line is a local regression.

3.1.3 $tn5x$ in southern Mali & Burkina Faso

Figure 12 shows the time series of April $tn5x$ (night-time temperatures) over southern Mali and Burkina Faso. In the CPC dataset, 2023 has an extremely low value and 2024 is below average; given the reported high nighttime temperatures, we believe this to be a data error, and disregard CPC for the analysis of minimum temperatures. In both ERA5 and MSWX the fitted model captures the increasing trend fairly well. The night-time temperatures over this region were unusual but not extreme: in ERA5 the return period is 11 years (95% interval: 5, 37) and in MSWX, 21 years (7, infinite). Because ERA5 is known to be provisional at the time of writing - and because the two datasets produce fairly similar return periods - we prioritise MSWX in this case, and assess this as a one-in-20-year event.

The five-day minimum temperatures over this region have increased by 2.03C in ERA5 (95% interval: 1.44, 2.69) and by 1.83C in MSWX (0.89, 2.77). These changes are of similar magnitude to those estimated for 5-day maximum temperatures in 3.1.1. The probability ratios for this event are again infinite in both ERA5 and MSWX. Plots of the linear trend in $tn5x$ as a function of GMST and of the effective return levels can be found in Figures A3 and A4 in the appendix.

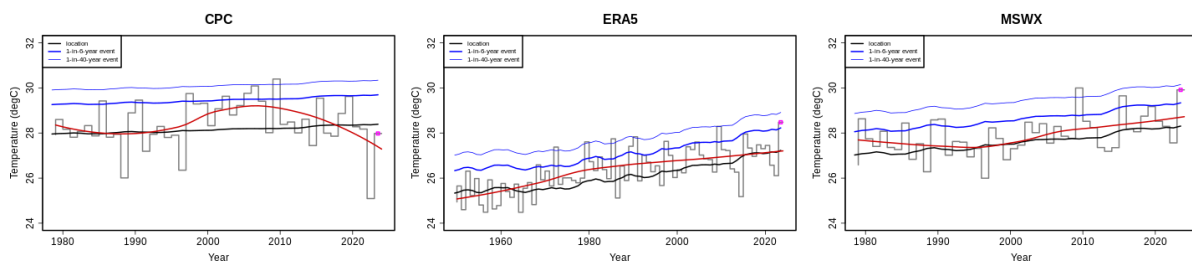


Figure 12: Time series of $tn5x$ (annual maxima of 5-day average of daily minimum temperatures averaged over southern Mali and Burkina Faso, as shown in Figure 5). The pink dot marks the 2024 event; the heavy black line indicates the mean of the fitted GEV model, and the blue lines indicate the expected return levels of 6- and 40-year events. The red line is a local regression.

3.2 Influence of modes of natural variability

In addition to testing the contribution of GMST to the intensity of the event, we also investigated whether there is evidence that the 2023-24 El Niño event enhanced the intensity or likelihood of the event. This was done by fitting a statistical model with both GMST and the DJF mean of the detrended Niño3.4 index as covariates, and estimating the probability ratio and change in intensity due to the current positive Niño phase compared to a neutral phase. The changes in intensity are shown in Table 2; the probability ratios are in Table A1 in the appendix. Both show weak evidence that the El Niño event has increased the intensity and likelihood of this heatwave, but only very slightly: temperatures were one or two tenths of a degree hotter than they would have been had Niño3.4 been in a neutral phase, but the signal is only consistently significant in maximum temperatures over Mali and Burkina Faso. However, we note that this only tests the influence of El Niño on five-day averages of maximum temperatures; the effect the number of heatwaves occurring during the season, or on the intensity of shorter-duration heatwaves, have not been investigated further due to time constraints.

Table 2: Changes in intensity of tx5x (°C) over each study region and in each dataset in response to the 2023-24 positive ENSO phase.

	tx5x, Mali/BF	tx5x, Sahel	tn5x, Mali/BF
CPC	0.15 (0.04, 0.26)	0.1 (-0.01, 0.21)	0.13 (-0.11, 0.22)
ERA5	0.15 (0.08, 0.22)	0.12 (0.03, 0.22)	0.12 (0.04, 0.22)
MSWX	0.12 (0.04, 0.23)	0.1 (-0.05, 0.21)	0.19 (0.05, 0.32)

4 Model evaluation

Climate models are evaluated against the three observational datasets for their ability to capture the observed distributions of tx5x and tn5x, and discarded if the ranges of the key parameters of the fitted non-stationary distribution do not overlap with those estimated from the observations. The models are labelled as ‘good’ if the best estimate falls within the bounds estimated from the observations; ‘reasonable’ if the confidence interval for the model overlaps with the range estimated from the observations; or ‘bad’ if the ranges do not overlap. Models are also evaluated in terms of how well they represent the spatial and seasonal patterns of precipitation and temperature over the region. If the model is ‘good’ for all criteria, we give it an overall rating of ‘good’. We rate the model as ‘reasonable’ or ‘bad’, if it is rated ‘reasonable’ or ‘bad’, respectively, for at least one criterion. In the tables below we show the results of the model validation for the three study regions. In each case, if more than five

models achieve a ‘good’ evaluation overall, then only these models are included in the attribution; if five models or fewer achieve this, then models deemed ‘reasonable’ are also included. Tables 3-5 show the model evaluation results for tx5x over Mali and Burkina Faso; for tx5x over the wider Sahel region; and for tn5x over Mali and Burkina Faso. In all cases, models deemed ‘good’ and ‘reasonable’ were included in the final analysis.

Table 3: Evaluation of the climate models considered for attribution analysis of tx5x over southern Mali and Burkina Faso. For each model, the best estimate of the scale parameters is shown, along with a 95% confidence interval for each, obtained via bootstrapping. The qualitative evaluation is shown in the right-hand column.

Model / Observations	Seasonal cycle	Spatial pattern	Sigma	Shape parameter	Conclusion
CPC			0.752 (0.535 ... 0.936)	-0.37 (-0.77 ... -0.068)	
ERA5			0.647 (0.521 ... 0.749)	-0.30 (-0.44 ... -0.17)	
MSWX			0.717 (0.476 ... 0.897)	-0.29 (-0.74 ... -0.057)	
ACCESS-CM2	reasonable	good	0.665 (0.462 ... 0.849)	-0.11 (-0.48 ... 0.19)	reasonable
ACCESS-ESM1-5	good	good	0.617 (0.471 ... 0.752)	-0.30 (-0.70 ... -0.080)	good
CanESM5	reasonable	good	0.861 (0.631 ... 1.05)	-0.39 (-0.63 ... -0.18)	reasonable
EC-Earth3	good	good	0.576 (0.431 ... 0.698)	-0.072 (-0.43 ... 0.16)	good
EC-Earth3-Veg	good	good	0.636 (0.449 ... 0.810)	-0.22 (-0.61 ... 0.17)	good
EC-Earth3-Veg-LR	reasonable	good	0.697 (0.490 ... 0.828)	-0.18 (-0.44 ... 0.075)	reasonable
INM-CM4-8	reasonable	good	0.496 (0.334 ... 0.621)	-0.32 (-0.66 ... -0.074)	reasonable
INM-CM5-0	good	good	0.696 (0.574 ... 0.804)	-0.28 (-0.68 ... -0.13)	good
MIROC6	good	reasonable	1.46 (0.973 ... 1.83)	0.013 (-0.26 ... 0.42)	bad
MPI-ESM1-2-HR	good	good	0.749 (0.546 ... 0.936)	-0.14 (-0.63 ... 0.27)	good
MPI-ESM1-2-LR	reasonable	good	0.958 (0.744 ... 1.16)	-0.29 (-0.55 ... -0.12)	reasonable
MRI-ESM2-0	good	good	0.880 (0.659 ... 1.06)	-0.28 (-0.75 ... -0.058)	good
NorESM2-LM	reasonable	good	0.714 (0.515 ... 0.864)	-0.29 (-0.53 ... -0.081)	reasonable
NorESM2-MM	reasonable	good	0.754 (0.562 ... 0.909)	-0.27 (-0.51 ... -0.052)	reasonable

Table 4: Evaluation of the climate models considered for attribution analysis of tx5x over the wider Sahel region. For each model, the best estimate of the scale parameters is shown, along with a 95% confidence interval for each, obtained via bootstrapping. The qualitative evaluation is shown in the right-hand column.

Model / Observations	Seasonal cycle	Spatial pattern	Sigma	Shape parameter	Conclusion
CPC			0.632 (0.384 ... 0.804)	-0.15 (-0.52 ... 0.34)	
ERA5			0.598 (0.460 ... 0.709)	-0.17 (-0.31 ... 0.014)	
MSWX			0.626 (0.369 ... 0.804)	-0.23 (-0.55 ... 0.35)	
ACCESS-CM2	reasonable	good	0.714 (0.438 ... 0.913)	-0.14 (-0.47 ... 0.23)	reasonable
ACCESS-ESM1-5	good	good	0.687 (0.522 ... 0.837)	-0.34 (-0.60 ... -0.14)	good
AWI-CM-1-1-MR	reasonable	good	0.755 (0.585 ... 0.879)	-0.27 (-0.57 ... -0.054)	reasonable

EC-Earth3	good	good	0.517 (0.401 ... 0.608)	-0.058 (-0.34 ... 0.14)	good
EC-Earth3-Veg	good	good	0.583 (0.437 ... 0.730)	-0.15 (-0.43 ... 0.080)	good
EC-Earth3-Veg-LR	reasonable	good	0.649 (0.449 ... 0.794)	-0.11 (-0.52 ... 0.25)	reasonable
INM-CM5-0	good	good	0.674 (0.512 ... 0.799)	-0.38 (-0.63 ... -0.20)	good
MIROC6	good	reasonable	1.28 (0.876 ... 1.54)	-0.049 (-0.40 ... 0.44)	bad
MPI-ESM1-2-HR	reasonable	good	0.751 (0.515 ... 0.900)	-0.16 (-0.55 ... 0.30)	reasonable
MPI-ESM1-2-LR	reasonable	good	0.722 (0.576 ... 0.855)	-0.16 (-0.50 ... 0.012)	reasonable
NorESM2-LM	reasonable	good	0.854 (0.607 ... 1.13)	-0.39 (-0.83 ... -0.12)	reasonable
NorESM2-MM	reasonable	good	0.926 (0.657 ... 1.09)	-0.45 (-0.73 ... -0.039)	reasonable

Table 5: Evaluation of the climate models considered for attribution analysis of $tn5x$ over southern Mali and Burkina Faso. For each model, the best estimate of the scale parameters is shown, along with a 95% confidence interval for each, obtained via bootstrapping. The qualitative evaluation is shown in the right-hand column.

Model / Observations	Seasonal cycle	Spatial pattern	Sigma	Shape parameter	Conclusion
ERA5			0.740 (0.578 ... 0.862)	-0.29 (-0.40 ... -0.11)	
MSWX			0.723 (0.520 ... 0.895)	-0.21 (-0.54 ... 0.061)	
ACCESS-CM2	reasonable	good	1.01 (0.740 ... 1.23)	-0.30 (-0.69 ... -0.014)	reasonable
ACCESS-ESM1-5	reasonable	good	0.956 (0.673 ... 1.06)	-0.89 (-0.91 ... -0.41)	reasonable
AWI-CM-1-1-MR	good	good	0.851 (0.605 ... 1.05)	-0.25 (-0.61 ... 0.0035)	good
CanESM5)	reasonable	good	1.34 (1.05 ... 1.57)	-0.30 (-0.64 ... -0.11)	reasonable
EC-Earth3	good	good	1.04 (0.782 ... 1.28)	-0.22 (-0.69 ... -0.082)	good
EC-Earth3-Veg	reasonable	good	1.39 (1.15 ... 1.74)	-0.35 (-0.73 ... -0.20)	reasonable
EC-Earth3-Veg-LR	good	good	1.37 (1.07 ... 1.68)	-0.29 (-0.61 ... -0.12)	good
INM-CM4-8	reasonable	good	1.14 (0.800 ... 1.42)	-0.53 (-0.89 ... -0.28)	reasonable
INM-CM5-0	reasonable	good	0.839 (0.655 ... 1.02)	-0.43 (-0.78 ... -0.19)	reasonable
MIROC6	good	reasonable	0.711 (0.510 ... 0.885)	-0.25 (-0.59 ... 0.049)	reasonable
MPI-ESM1-2-HR	good	good	0.750 (0.474 ... 0.936)	-0.24 (-0.55 ... 0.12)	good
MPI-ESM1-2-LR	good	good	0.819 (0.614 ... 0.980)	-0.30 (-0.57 ... -0.10)	good
MRI-ESM2-0	good	good	0.583 (0.434 ... 0.713)	-0.11 (-0.46 ... 0.10)	good
NorESM2-LM	reasonable	good	1.65 (1.22 ... 1.94)	-0.36 (-0.67 ... -0.054)	reasonable
NorESM2-MM	reasonable	good	1.38 (1.01 ... 1.69)	-0.44 (-0.82 ... -0.27)	reasonable

5 Multi-method multi-model attribution

Tables 6-8 show probability ratios (PR) and changes in intensity (ΔI) for the observational data products and for those models that passed evaluation for each index.

Table 6: Event magnitude, probability ratio and change in intensity for 100-year tx5x over southern Mali and Burkina Faso for observational datasets and each model that passed evaluation: (a) from preindustrial climate to the present and (b) from the present to 2C above preindustrial.

		(a) -1.2C vs present		(b) Present vs +0.8C	
Model / Observations	100-year event (°C)	Probability ratio	Change in intensity (°C)	Probability ratio	Change in intensity (°C)
CPC	43.8	∞ (6.4 ... ∞)	2.3 (0.75 ... 3.3)		
ERA5	42.6	∞ (1.4e+4 ... ∞)	1.6 (1.2 ... 2.1)		
MSWX	42.0	∞ (38 ... ∞)	2.2 (1.2 ... 3.4)		
ACCESS-CM2	43.9	9.2e+3 (32 ... ∞)	1.5 (1.1 ... 2.0)	10 (6.4 ... 1.2e+2)	1.1 (0.96 ... 1.2)
ACCESS-ESM1-5	43.7	∞ (∞ ... ∞)	1.7 (1.4 ... 2.0)	43 (18 ... 1.6e+3)	1.1 (0.94 ... 1.1)
CanESM5	48.5	∞ (∞ ... ∞)	1.2 (0.98 ... 1.6)	15 (8.5 ... ∞)	0.84 (0.76 ... 0.94)
EC-Earth3	43.4	∞ (1.1e+2 ... ∞)	1.4 (1.2 ... 1.7)	14 (7.5 ... ∞)	0.94 (0.86 ... 1.0)
EC-Earth3-Veg	42.9	∞ (∞ ... ∞)	1.5 (1.2 ... 1.7)	15 (9.6 ... 69)	1.0 (0.90 ... 1.1)
EC-Earth3-Veg-LR	42.7	∞ (∞ ... ∞)	1.7 (1.4 ... 2.0)	21 (13 ... 6.7e+3)	1.2 (1.0 ... 1.3)
INM-CM4-8	44.0	∞ (∞ ... ∞)	1.6 (1.3 ... 1.9)	97 (35 ... 1.3e+5)	0.99 (0.90 ... 1.1)
INM-CM5-0	43.6	∞ (∞ ... ∞)	1.3 (0.91 ... 1.7)	21 (11 ... ∞)	0.86 (0.74 ... 0.98)
MPI-ESM1-2-HR	44.4	∞ (50 ... ∞)	1.3 (0.93 ... 1.7)	12 (6.8 ... 1.5e+2)	0.88 (0.73 ... 1.0)
MPI-ESM1-2-LR	43.7	∞ (∞ ... ∞)	1.7 (1.1 ... 2.2)	33 (13 ... ∞)	1.0 (0.85 ... 1.2)
MRI-ESM2-0	47.3	∞ (∞ ... ∞)	1.6 (1.1 ... 2.0)	21 (9.8 ... ∞)	0.95 (0.80 ... 1.1)
NorESM2-LM	43.0	1.9e+3 (6.8 ... ∞)	1.4 (0.79 ... 2.1)	12 (5.4 ... ∞)	0.94 (0.67 ... 1.2)
NorESM2-MM	42.3	∞ (41 ... ∞)	1.3 (0.81 ... 1.9)	10 (6.7 ... 19)	1.1 (0.93 ... 1.3)

Table 7: Event magnitude, probability ratio and change in intensity for 30-year tx5x over the wider Sahel region for observational datasets and each model that passed evaluation: (a) from preindustrial climate to the present and (b) from the present to 2C above preindustrial.

		(a) -1.2C vs present		(b) Present vs +0.8C	
Model / Observations	30-year event (°C)	Probability ratio	Change in intensity (°C)	Probability ratio	Change in intensity (°C)
CPC	43.2	5.2e+3 (2.2 ... ∞)	1.8 (0.66 ... 2.8)		
ERA5	41.4	1.7e+2 (13 ... ∞)	1.5 (1.0 ... 1.9)		
MSWX	41.6	∞ (5.7 ... ∞)	1.8 (1.0 ... 2.6)		
ACCESS-CM2	42.4	1.4e+4 (58 ... ∞)	1.4 (1.1 ... 2.0)	6.8 (5.1 ... 20)	1.0 (0.91 ... 1.1)
ACCESS-ESM1-5	42.2	∞ (6.9e+3 ... ∞)	1.5 (1.2 ... 1.8)	11 (7.8 ... 29)	0.99 (0.89 ... 1.1)
AWI-CM-1-1-MR	43.2	∞ (∞ ... ∞)	1.2 (0.96 ... 1.5)	8.5 (6.1 ... 32)	0.83 (0.72 ... 0.93)

EC-Earth3	41.9	1.0e+6 (84 ... ∞)	1.4 (1.2 ... 1.6)	8.5 (5.9 ... 3.7e+2)	0.96 (0.88 ... 1.0)
EC-Earth3-Veg	41.9	∞ (8.1e+2 ... ∞)	1.6 (1.4 ... 1.8)	11 (7.9 ... 21)	1.0 (0.95 ... 1.1)
EC-Earth3-Veg-LR	41.3	1.0e+6 (1.3e+2 ... ∞)	1.4 (1.2 ... 1.8)	8.2 (6.0 ... 30)	1.1 (1.0 ... 1.2)
INM-CM5-0	42.6	∞ (2.6e+6 ... ∞)	1.2 (0.83 ... 1.6)	9.1 (6.7 ... 23)	0.86 (0.74 ... 0.96)
MPI-ESM1-2-HR	53.5	4.3e+2 (21 ... ∞)	1.3 (0.95 ... 1.6)	7.1 (5.0 ... 15)	0.91 (0.75 ... 1.0)
MPI-ESM1-2-LR	43.0	6.8e+12 (47 ... ∞)	1.4 (0.93 ... 1.8)	8.5 (5.5 ... 78)	0.87 (0.73 ... 1.0)
NorESM2-LM	42.0	∞ (17 ... ∞)	1.4 (0.54 ... 2.1)	6.4 (4.4 ... ∞)	0.98 (0.64 ... 1.2)
NorESM2-MM	41.3	∞ (9.8e+5 ... ∞)	1.5 (0.90 ... 2.1)	6.4 (5.0 ... 9.2)	1.3 (1.1 ... 1.4)

Table 8: Event magnitude, probability ratio and change in intensity for 20-year $tn5x$ over southern Mali and Burkina Faso for observational datasets and each model that passed evaluation: (a) from preindustrial climate to the present and (b) from the present to 2C above preindustrial.

		(a) -1.2C vs present		(b) Present vs +0.8C	
Model / Observations	20-year event (°C)	Probability ratio	Change in intensity (°C)	Probability ratio	Change in intensity (°C)
ERA5	28.5	∞ (4.7e+2 ... ∞)	2.0 (1.4 ... 2.7)		
MSWX	29.9	∞ (6.2 ... ∞)	1.8 (0.89 ... 2.8)		
ACCESS-CM2	29.3	∞ (1.1e+3 ... ∞)	1.9 (1.4 ... 2.8)	7.5 (5.6 ... 15)	1.3 (1.2 ... 1.5)
ACCESS-ESM1-5	29.5	∞ (∞ ... ∞)	1.8 (1.4 ... 2.2)	19 (11 ... 1.4e+2)	1.1 (0.99 ... 1.2)
AWI-CM-1-1-MR	34.2	∞ (2.6e+2 ... ∞)	1.6 (1.3 ... 2.0)	6.9 (5.3 ... 18)	1.1 (1.0 ... 1.2)
CanESM5	29.8	∞ (∞ ... ∞)	2.1 (1.5 ... 2.6)	8.8 (6.0 ... 3.7e+2)	1.2 (1.1 ... 1.4)
EC-Earth3	26.3	∞ (6.3e+2 ... ∞)	1.9 (1.4 ... 2.3)	4.8 (3.9 ... 9.0)	1.3 (1.1 ... 1.5)
EC-Earth3-Veg	26.4	∞ (∞ ... ∞)	2.0 (1.6 ... 2.4)	5.6 (4.6 ... 9.2)	1.4 (1.2 ... 1.6)
EC-Earth3-Veg-LR	26.1	∞ (4.2e+3 ... ∞)	2.2 (1.7 ... 2.8)	6.0 (4.7 ... 15)	1.6 (1.4 ... 1.8)
INM-CM4-8	28.0	∞ (∞ ... ∞)	2.3 (1.4 ... 2.6)	16 (9.9 ... ∞)	1.4 (1.2 ... 1.6)
INM-CM5-0	27.9	∞ (∞ ... ∞)	1.9 (1.5 ... 2.3)	12 (7.7 ... 4.4e+2)	1.2 (1.1 ... 1.3)
MIROC6	30.1	6.4e+6 (97 ... ∞)	2.0 (1.5 ... 2.7)	8.1 (5.7 ... 16)	1.2 (1.0 ... 1.4)
MPI-ESM1-2-HR	34.1	∞ (1.6e+3 ... ∞)	2.2 (1.8 ... 2.6)	13 (9.2 ... 65)	1.3 (1.2 ... 1.5)
MPI-ESM1-2-LR	32.9	∞ (∞ ... ∞)	2.0 (1.6 ... 2.4)	13 (8.5 ... 38)	1.2 (1.0 ... 1.3)
MRI-ESM2-0	32.8	∞ (2.0e+2 ... ∞)	2.0 (1.6 ... 2.3)	11 (6.6 ... 34)	1.1 (0.95 ... 1.2)
NorESM2-LM	29.9	∞ (3.1 ... ∞)	1.3 (0.21 ... 2.5)	3.6 (2.6 ... 10)	0.88 (0.46 ... 1.2)
NorESM2-MM	30.0	∞ (∞ ... ∞)	2.0 (0.71 ... 2.5)	4.9 (4.1 ... 8.5)	1.6 (1.4 ... 1.8)

6 Hazard synthesis

For both regions described in the event definition (Section 1.1) above we evaluate the influence of anthropogenic climate change on the 5-day average maximum temperatures and 5-day average minimum temperatures in April by calculating the probability ratio as well as the change in intensity using observation-based data products and climate models. Models which do not pass the evaluation tests described in Section 4 are excluded from the analysis. The aim is to synthesise results from models that pass evaluation along with the observations-based products (Section 5), to give an overarching attribution statement. Figures 13,15 and 17 show the changes in intensity for the observations (blue) and models (red); 14, 16 and 18 show the probability ratios, on a log scale. Before combining the changes into a synthesised assessment, first, a representation error is added (in quadrature) to the observations, to account for the difference between observations-based datasets that cannot be explained by natural variability. This is shown in these figures as white boxes around the light blue bars. The dark blue bar shows the average over the observation-based products. Next, a term to account for intermodel spread is added (in quadrature) to the natural variability of the models. This is shown in the figures as white boxes around the light red bars. The dark red bar shows the model average, consisting of a weighted mean using the (uncorrelated) uncertainties due to natural variability plus the term representing intermodel spread (i.e., the inverse square of the white bars). Observation-based products and models are combined into a single result in two ways. Firstly, we neglect common model uncertainties beyond the intermodel spread that is depicted by the model average, and compute the weighted average of models (dark red bar) and observations (dark blue bar): this is indicated by the magenta bar. As, due to common model uncertainties, model uncertainty can be larger than the intermodel spread, secondly, we also show the more conservative estimate of an unweighted, direct average of observations (dark red bar) and models (dark blue bar) contributing 50% each, indicated by the white box around the magenta bar in the synthesis figures.

For all three event definitions, the likelihood of an event of the magnitude observed to occur in the 1.2°C cooler climate is virtually impossible in both the observation-based products and in most climate models, rendering the change in probability ratio (PR) infinite (Tables 6-8a). We thus do not show the change in likelihood between the present and a 1.2°C cooler climate but report the events to have been impossible to occur without climate change.

For all three events there is a strong increase in intensity due to human induced climate change. For the smaller region the intensity change in 5-day t_{max} is larger in the observations than in the models but well within the uncertainties. For 5-day t_{min} as well as 5-day t_{max} in the larger region there are no systematic differences between the models and observations. In all three cases, we therefore report the best-estimate of the synthesised results as the main result which is an increase of 1.5°C for 5-day t_{max} in Mali/Burkina Faso, an increase of 2°C for 5-day t_{min} in the same region and an increase of 1.4°C for 5-day t_{max} over the larger Sahel region.

When repeating the analysis comparing the present climate at 1.2°C warmer than pre-industrial with a future 0.8°C warmer climate (2°C global warming since pre-industrial times) there is an additional increase of about 1°C for 5-day maximum t_{max} in both regions while the increase in the intensity of 5-day minimum temperatures in Mali/Burkina Faso is again largest with a best estimate of 1.26°C. As expected and discussed in section 1.2, the trend in minimum temperatures is thus different to that in maximum temperatures.

For the 2°C global warming since pre-industrial times we also calculate the change in likelihood compared to the present climate and find for all three event definitions an increase of approx. a factor 10. While individual models show slightly larger or smaller changes there is a broad agreement around the order of magnitude, thus we report a factor 10 increase for all regions.

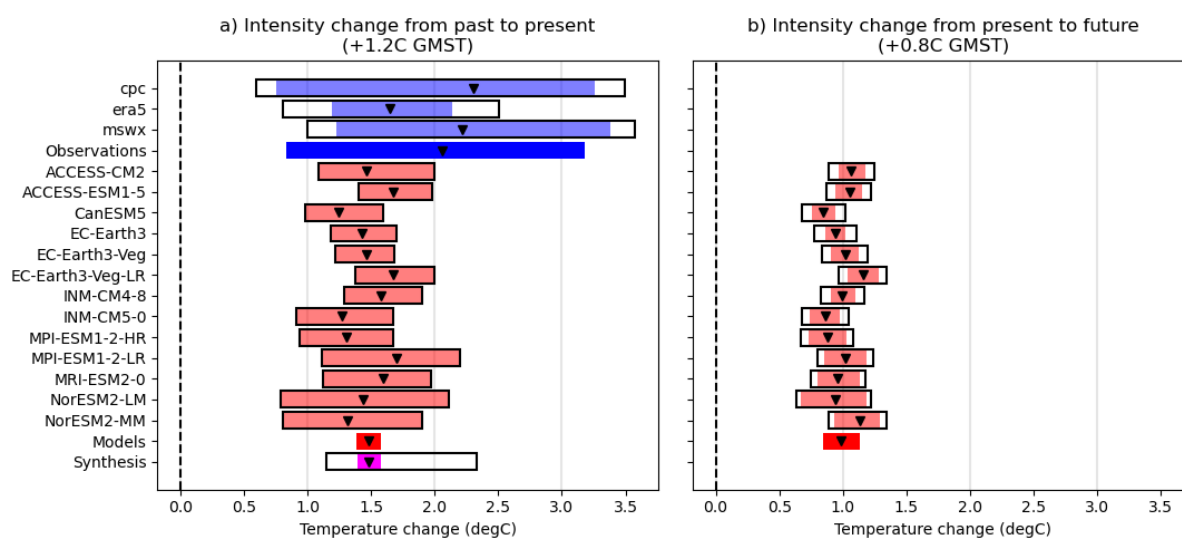


Figure 13: Synthesis of change in intensity (°C) in April tx5x in southern Mali / Burkina Faso between (a) the current climate and a 1.2C cooler climate and (b) the current climate and a 0.8C warmer climate (ie. with total warming of 2C).

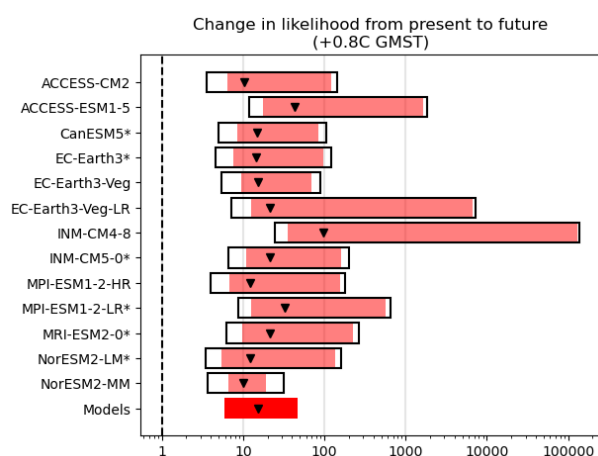


Figure 14: Synthesis of probability ratios for April tx5x in southern Mali / Burkina Faso between the current climate and a 0.8C warmer climate (ie. with total warming of 2C). Models marked with a * originally had an infinite upper bound, which was replaced with a value representing a 6-sigma interval based on the finite lower bound.

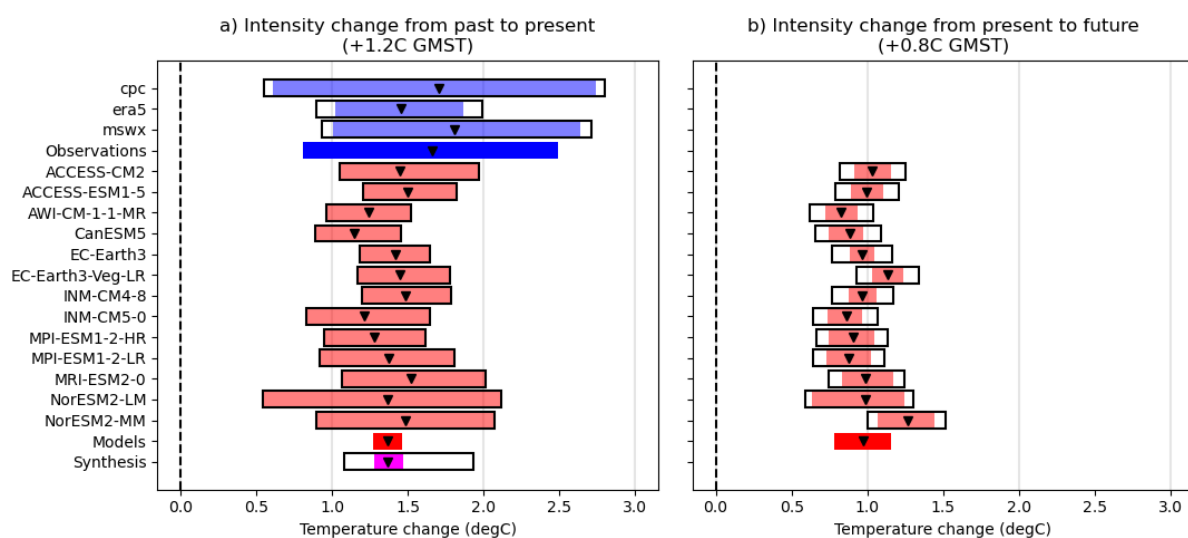


Figure 15: Synthesis of change in intensity (°C) in April tx5x in wider Sahel region between (a) the current climate and a 1.2C cooler climate and (b) the current climate and a 0.8C warmer climate (ie. with total warming of 2C).

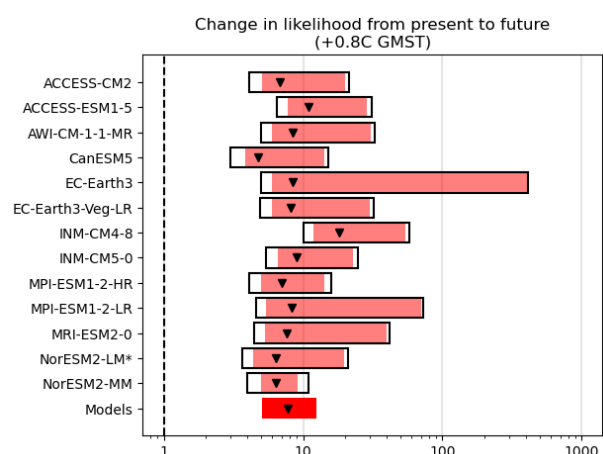


Figure 16: Synthesis of probability ratios for April tx5x in wider Sahel region between the current climate and a 0.8C warmer climate (ie. with total warming of 2C). Models marked with a * originally had an infinite upper bound, which was replaced with a value representing a 6-sigma interval based on the finite lower bound.

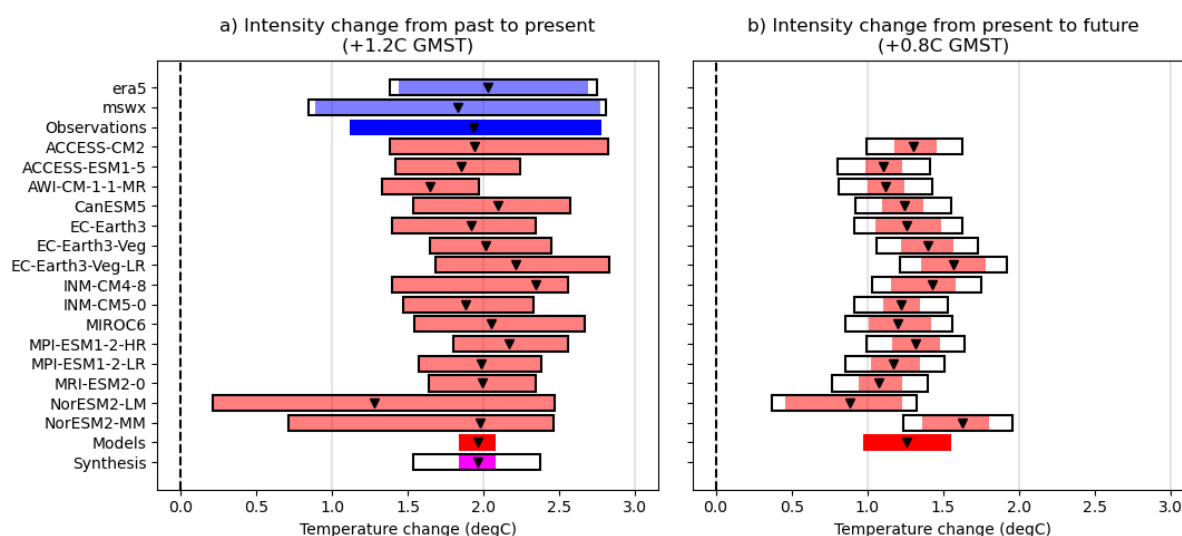


Figure 17: Synthesis of change in intensity ($^{\circ}\text{C}$) in April $tn5x$ in southern Mali / Burkina Faso between (a) the current climate and a 1.2C cooler climate and (b) the current climate and a 0.8C warmer climate (ie. with total warming of 2C).

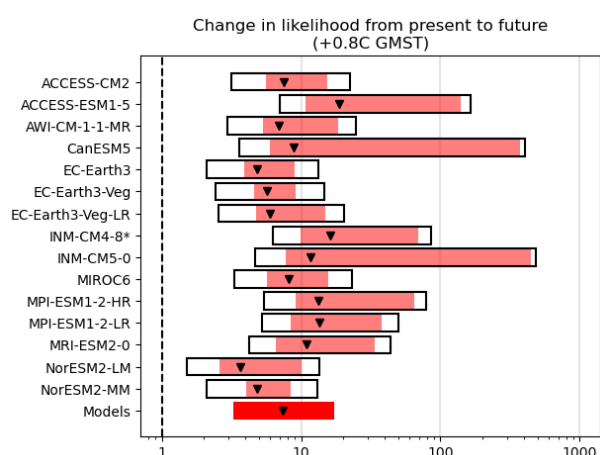


Figure 18: Synthesis of probability ratios for April $tn5x$ in southern Mali / Burkina Faso between the current climate and a 0.8C warmer climate (ie. with total warming of 2C). Models marked with a * originally had an infinite upper bound, which was replaced with a value representing a 6-sigma interval based on the finite lower bound.

7 Vulnerability and exposure

Globally, extreme heat is amongst the deadliest natural hazards, with thousands of people dying from heat-related causes each year ([The Lancet, 2021](#)). However, the full impact of extreme heat is often not known until weeks or months afterwards, once death certificates are collected, or scientists can analyze excess deaths. In many cases, the full extent of its impact on human health is never truly known because heat-related deaths are often attributed to other causes like kidney failure or cardiac arrest, even though it may not have occurred had the high temperatures not exacerbated someone's pre-existing condition,

or they are not counted at all. While excess deaths should show this, many countries are lacking full death records. Despite this, in near real-time, a surge in hospital admissions and 102 fatalities were reported from the Gabriel Touré hospital in Bamako, Mali between 1-4 April, which is significantly more than expected (in April 2023, it recorded 130 over the entire month) and many of which likely connected to the extreme heat ([Bahati, 2024](#)). Furthermore, up to 44 bodies were buried in one cemetery in Bamako on 5 April after the weekly service ([DW, 2024](#)).

Despite limited available data on heat risk, particularly in Mali, there is evidence from existing research that exposure to high temperatures has a negative impact on health, disrupted education, as well as, income and productivity ([Dasgupta & Robinson, 2023](#)).

Extreme heat is a significant risk factor for deaths related to cardiovascular diseases in both countries of focus. These are becoming more common due to the epidemiological transition in the region, in part connected to local diets increasingly consisting of processed foods and carbohydrates which moves key morbidities from infectious to non-communicable diseases ([Arisco et al., 2023](#); [Macia et al., 2017](#); [Hill, 2010](#)). People suffering from chronic conditions (such as albinism or leprosy) are also shown to be among the most vulnerable to extreme heat in major cities such as Ouagadougou ([Somdakouma et al., 2024](#)). In Mali, heat-related mortality is projected to increase fivefold by 2080 under a high-emissions scenario, up from 2,5 to 12 fatalities annually per 100,000 people ([Tomalka et al., 2021](#)). In Burkina Faso, where indoor temperature in the most vulnerable households can be up to 10C hotter than in other houses ([Pohl et al., 2021](#)), sleep duration also decreases significantly with higher heat exposure, and daily activity patterns are affected by temperature changes ([Koch et al., 2023](#)). High temperatures also increase heart and respiratory rates. Research further suggests that women spend less time breastfeeding during the hottest times of the year, putting infants and young children at greater risk of heat-related illnesses ([Part et al., 2022](#)). Pregnant women and newborns are particularly vulnerable to the impacts of extreme heat due to physiological reasons, which can lead to maternal hypertension, premature birth, low birth weight, and stillbirth ([Kadio et al., 2024](#)). Climate change also exacerbated heat-related neonatal deaths. A study by Diboulo et al. ([2012](#)) showed that under five children are a particular at-risk group of heat mortality in rural Burkina Faso. Moreover, vulnerable and marginalized communities such as older adults, people living with disabilities, and individuals with pre-existing medical conditions may face heightened exposure and lack the resources to mitigate compounding vulnerabilities during extreme heat ([IFRC et al., 2022](#)).

During periods of extreme heat, children and adolescents may experience disruptions to their education due to school closures or reduced time in school, with research indicating that heat can adversely impact learning outcomes ([IFRC et al., 2022](#); [Luthen et al., 2021](#)). During this heatwave, authorities in Mali advised that school hours are limited to protect students from the extreme temperatures ([African Perceptions, 2024](#)). As such, to safeguard the well-being of primary school pupils, school hours were reduced, although this recognizes the importance of shielding children from the scorching conditions, it also prevents continuity in learning ([African Perceptions, 2024](#)). Furthermore, children from low-income households are more likely to reside in areas, such as informal settlements, that are significantly hotter and impacted by micro-heat islands, and who are less likely to have access to mitigation mechanisms such as air-conditioning ([Luthen et al., 2021](#); [Scott et al., 2017](#)). As such, exposure to extreme heat can exacerbate inequalities faced by children and adolescents (*ibid*). Mali and Burkina have been facing conflicts for many years with a high number of internally displaced people in extreme living conditions and who also constitute another vulnerable group to extreme heat associated with impact on health.

Individuals who are employed in the informal sector or work outdoors such as in agriculture, construction, or market vendors have high exposure to heat and may lack the options to reduce exposure through options such as reduced work hours, breaks, or cooling mechanisms ([IFRC et al., 2022](#)). Moreover, their capacity to adjust their working hours is also expected to be limited. This can have severe impacts on their health ([ibid](#)). On the other hand, if they opt to skip days or reduce their working hours, this can adversely affect productivity and income ([ibid](#)). In addition to health, extreme heat significantly increases the water and energy demand, leading to prolonged shortages of both resources ([Sidibe, 2024](#)).

This rapid analysis examines the preparedness, spatial planning, and adaptation of critical infrastructure in Burkina Faso and Mali to extreme heat. While the study has two event definitions, one of which is the wider Sahelian region, this section focuses on a smaller area in which the reported impacts were concentrated. Further research will be essential to learn from the event.

7.1 Heat action

In the days leading up to this period of extreme heat, both the Burkina Faso ([ANAM-BF 2024](#)) and Mali ([Mali Meteo, 2024](#)) National Meteorological agencies issued heat wave warnings for the general public. As mentioned in the previous section, authorities in Mali advised citizens to seek refuge in well-ventilated areas, and as mentioned in the previous section, took action to safeguard students from extreme heat ([African Perceptions, 2024](#)). In a public broadcast on the state-owned Office de Radio et Television du Mali (ORTM), the government emphasized that young and older adults are the most vulnerable to the deadly heat ([African Perceptions, 2024](#)). Neither of the countries appear to have comprehensive heat action plans or emergency protocols in place to reduce risks from extreme heat. However, Burkina Faso through its Red Cross National Society has developed a heat wave early action protocol for the city of Ouagadougou which is currently undergoing the validation process.

In Burkina Faso, the extreme heat raised serious concerns among health professionals who have mobilized health facilities and professionals to protect vulnerable populations and coordinate a comprehensive response ([Kambou, 2024](#)). The Ministry of Health and Public Hygiene has strongly advised the population to take precautions, particularly by staying hydrated and watching over older adults, who may not always feel thirsty ([Kambou, 2024](#)). It further emphasized the need for anticipation, better diagnosis, and rapid treatment of cases to control the situation in health facilities ([Xinhua French, 2024](#)). This coordinated effort involves various health stakeholders, who have discussed aspects such as patient reception conditions and staff working conditions, as well as case management strategies ([Kambou, 2024](#)).

The particularity of this period of extreme heat is also that it occurred during the holy month of Ramadan, in a region with many Muslims. The practice of fasting during Ramadan can present health challenges when coinciding with extreme heat stress. For more than one billion Muslims, practicing their religion means adhering to the basic tenets, known as the Five Pillars of Islam ([Saeed et al., 2021](#)). Fasting during the holy month of Ramadan is one of these tenets. Ramadan is the ninth month in the Islamic calendar, which is based on the 354-day lunar cycle. During fasting, observers of Islam abstain from some basic needs during daylight hours, including food and fluids. This may have contributed to exacerbating the impacts as some usual cooling strategies, such as drinking water and consuming other cool beverages, could not be used.

7.2 Urban planning for heat

The rapid urbanization and sprawl in Mali and Burkina Faso, have led to significant increases in urban heat island (UHI), notably in Ouagadougou, Bamako, Bobo-Dioulasso, and Sikasso, and especially in the new neighbourhoods hosting the most vulnerable communities ([Di Leo et al., 2015](#); [Ouedraogo et al., 2023](#)). Exacerbated by a reduction in green spaces within urban areas, this has had a cascading negative impact on the heat resilience of these cities and their populations ([Fomba et al., 2024](#)). The integration of green infrastructure, particularly nature-based solutions, into urban planning is essential for building resilient cities in the face of climate change. Vegetation can help mitigate the urban heat island effect through shading and evapotranspiration ([Fomba et al., 2024](#)).

In Mali, the cities of Bamako and Sikasso have experienced significant land use changes over the past three decades. According to a recent study by Fomba et al. ([2024](#)), the results of a land use/land cover analysis showed that most of the vegetation classes, particularly urban green spaces, have been converted into built-up and bare land in both cities since 1990. In Bamako, the built-up land has risen from 5,421 hectares in 1990 to 13,350 hectares in 2020, while in Sikasso, it has increased from 929 hectares to 2,213 hectares during the same period. To address the issue of heat risk in these rapidly growing cities, Fomba et al. ([2024](#)) recommended promoting sustainable land use systems, and involving urban planners and the public.

In Burkina Faso, studies have shown that vegetated areas in cities like Ouagadougou and Bobo-Dioulasso experience significantly lower temperatures compared to built-up areas ([Holmer et al., 2012](#)). This demonstrates how preserving and expanding green infrastructure such as parks, urban forests, and urban agriculture can help reduce the urban heat island effect. Mitigating heat risk in Burkina Faso's cities requires urban planning strategies that prioritize increasing green spaces and vegetation cover. Additionally, urban planners should promote building designs and materials with high thermal inertia to moderate indoor temperatures and reduce heat exposure for residents ([Di Leo et al., 2015](#)). Informal settlements with inadequate housing are particularly vulnerable to heat stress, which suggests that improving ventilation, insulation, and shading should be a priority. Controlling the urban sprawl and densification is also crucial, as the rapid, unplanned expansion of built-up areas exacerbates heat risk, notably by replacing vegetated land with impervious surfaces ([Ouedraogo et al., 2023](#)). Integrated land-use planning that balances urban development with environmental conservation can help create more sustainable and climate-resilient cities.

There is a gap in the literature on aspects of urban planning and design (e.g. infrastructure) in cities in Burkina Faso and Mali that would warrant further study to fully understand how the urban built environment during heatwaves impacts residents.

7.3 Adaptation for electricity, water, and health systems

Mali and Burkina Faso are facing significant challenges in adapting their critical infrastructure to cope with the increasing frequency and intensity of heat waves driven by climate change.

Both countries are grappling with aging and inadequate electricity generation capacity, leading to frequent and prolonged power outages (see e.g. [Risemberg, 2023](#); [Dembele, 2024](#); [The Citizen, 2023](#); [Eagle News, 2023](#); [Africa News, 2023](#)). In Mali, the state-owned utility Energy du Mali (EDM) is struggling to meet the growing demand, with power cuts lasting several hours, including during extreme heat when cooling is crucial ([Africa News, 2023](#); [Dembele, 2024](#)). Burkina Faso experiences several outages per year, often due to load-shedding programs to prevent grid collapse ([Tinto, 2017](#)). Increased

electricity demand during periods of extreme heat exacerbates the strain on these fragile systems. This year in particular, both Burkina Faso and Mali experienced an unusual electricity crisis with prolonged and unpredictable power cuts which prompted large complaints from users as well as several media outings of the directors of the energy companies ([RTB 2024](#), [Jeune Afrique 2024](#)).

Access to safe drinking water is limited in both countries, with less than half of the population in Burkina Faso having access ([Kadio et al., 2024](#)). Extreme heat can further reduce water supply, as seen in Mali, where the International Committee of the Red Cross (ICRC) has had to support existing infrastructure during periods of drought and extreme heat ([ICRC, 2019](#)). Lack of running water can exacerbate the impacts of extreme heat, particularly in urban areas where risks are compounded by limited shade and poor housing conditions ([Kadio et al., 2024](#)).

Finally, the healthcare systems in both countries are already strained, with Burkina Faso facing challenges due to armed conflicts, leading to limited access to healthcare for over 500,000 people ([ICRC, 2019](#)). Increased demand for healthcare services during heat waves may overwhelm the limited facilities and resources, making it difficult to adequately meet the needs of the affected population. Policymakers in Burkina Faso have the knowledge and willingness to undertake adaptation measures. For example, a decision has just been made to provide free care to patients admitted to the main hospital of the country with hyperthermia or heat stroke ([Yalgago Teaching Hospital, 2024](#)). However, they face institutional barriers such as insufficient financial resources, bureaucracy, and diverging priorities ([Sorgho et al., 2023](#)). Overcoming these barriers will require systemic reforms, including investigating power dynamics, conducting research, building lobbying groups, and articulating the economic benefits of a climate-resilient healthcare system ([Sorgho et al., 2023](#)).

7.4 V&E conclusion

While Burkina Faso and Mali are both countries with populations that are acclimated to high temperatures, the length and severity of this heatwave made it so that people had a difficult time coping, as evidenced by the reported impacts. Therefore, extreme heat is a significant threat in Burkina Faso and Mali, with particularly vulnerable populations including older adults, children, and people with chronic medical conditions. The studied extreme heat coincided with Ramadan (fasting) and power cuts, which compounded the risk for vulnerable groups and even those not traditionally considered vulnerable. Even minimum temperatures, overnight, remained relatively high, making it so that people did not get a break from the heat. The power cuts further made it difficult for those with access to air conditioning to use it, thus reducing their coping capacity.

Both countries lack comprehensive heat action plans and emergency protocols, though Burkina Faso is currently in the process of validating a heat wave early action protocol for the capital city, Ouagadougou. Rapid urbanization and loss of green spaces in cities such as Bamako and Ouagadougou have increased the urban heat island effect. Coupled with high vulnerability, this highlights the need for sustainable urban planning that integrates green spaces, and building designs that account for high temperatures. Critical infrastructure such as electricity, water, and healthcare systems in the countries are struggling to adapt to the increasing frequency and intensity of extreme heat, requiring systemic reforms and increased investment to ensure reliable access and service delivery.

Data availability

Time series used in this study are available via KNMI's climate explorer.

References

All references are given as hyperlinks in the text.

Appendix

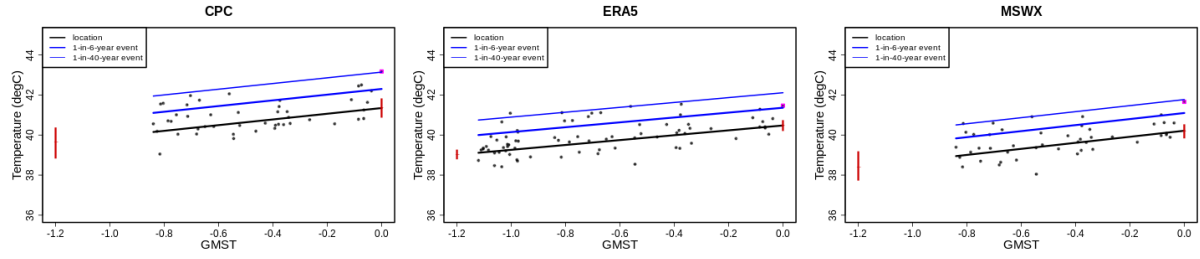


Figure A1: Linear trend in tx5x over the wider Sahel region as a function of GMST. The thick black line denotes the location parameter of the fitted distribution, and the blue lines show estimated 6- and 40-year return levels. The vertical lines show the 95% confidence interval for the location parameter for the 2024 climate and a hypothetical 1.2°C cooler climate. The 2024 observation is highlighted in magenta.

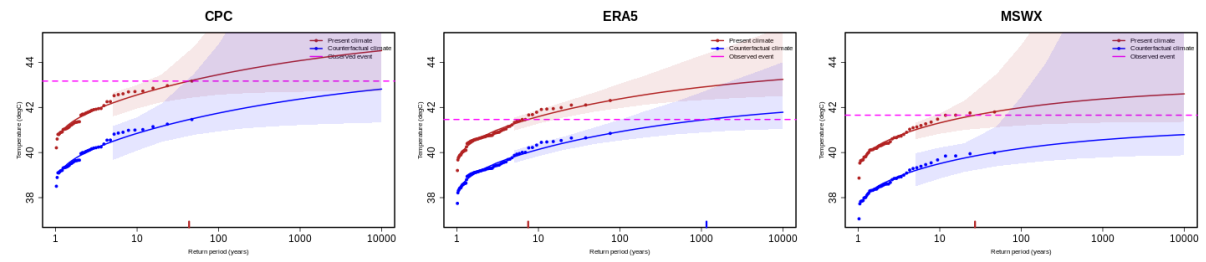


Figure A2: Estimated return levels for tx5x over the wider Sahel region at 2024 GMST (red lines) and 1.2°C lower GMST (blue line) according to the fitted GEV. Shaded regions represent 95% confidence intervals obtained via a bootstrapping procedure. The pink line shows the observed value of the 2024 event.

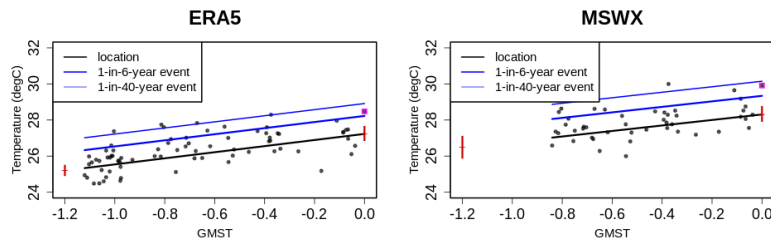


Figure A3: Linear trend in tn5x over southern Mali and Burkina Faso as a function of GMST. The thick black line denotes the location parameter of the fitted distribution, and the blue lines show estimated 6- and 40-year return levels. The vertical lines show the 95% confidence interval for the location parameter for the 2024 climate and a hypothetical 1.2°C cooler climate. The 2024 observation is highlighted in magenta.

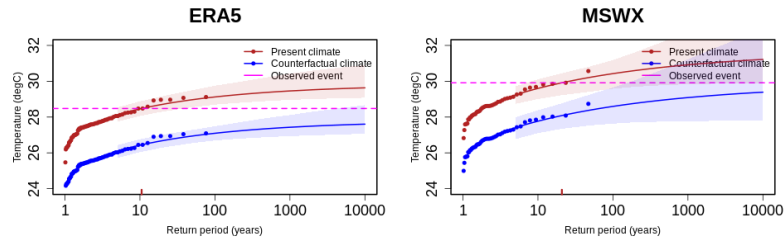


Figure A4: Estimated return levels for tx5x over the wider Sahel region at 2024 GMST (red lines) and 1.2C lower GMST (blue line) according to the fitted GEV. Shaded regions represent 95% confidence intervals obtained via a bootstrapping procedure. The pink line shows the observed value of the 2024 event.

Table A1: Probability ratio (factor change in the likelihood of experiencing a value of tx5x at least as extreme as the 2024 event) over each study region and in each dataset in response to 2023-24 positive ENSO phase.

	tx5x, Mali/BF	tx5x, Sahel	tn5x, Mali/BF
CPC	Inf (1.15, Inf)	1.36 (0.98, 39.07)	1.03 (0.94, 1.07)
ERA5	1.98 (1.44, Inf)	1.31 (1.07, 1.67)	1.31 (1.09, 1.9)
MSWX	2.3 (1.16, Inf)	1.49 (0.93, Inf)	1.77 (1.09, Inf)